STRESS TESTING FRAMEWORK BASED ON MARKET RISK MODELS: ANALYSES ON FOREIGN EXCHANGE AND STOCK MARKETS IN THAILAND

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An Independent Study
Submitted in Partial Fulfillment of the Requirements
for the Degree of Master of Science (Finance)

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By

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Abstract

This study follows Alexander and Sheedy (2008) of estimating stress test based on market risk model to investigate Thai financial market, i.e., SET50 index, and long and short positions in USD/THB currency pair. There are 4 risk models in this study which are unconditional normal, conditional normal, conditional Student's *t*, and conditional empirical risk models. For SET50 index and long and short positions in USD/THB, both backtesting and stress test results support the use of conditional risk models for estimating risk. While the conditional Student's *t* risk model can estimate appropriate stress losses for all data when compare with the worst historical loss over 3-day and 10-day, the VaR-based regulatory capital estimated from the model could be problematic when considering applying this model with these financial data.

I. Introduction

Financial institutions are required by regulators to have sufficient capital to cover possible risk. For regulators and loan originators, capital must be sufficiently held by financial institutions to make sure that they can cover losses that may occur from their activities or unexpected adverse situations. For financial institutions and shareholders, however, reserving capital means opportunities cost. To meet these contradictory objectives, model for valuing risk is then introduced to evaluate possible losses of the institutions and to recommend sufficient capital required to meet that losses. Therefore, if the risk model is accurate, only the amount of capital suggested by the model is adequate for possible uncertainty. In that case, creditors and regulators do not have to worry about default risk or bankruptcy while financial institutions do not have to reserve too much capital and can use excess reserves to generate more income.

In reality, however, it is not that easy. Several studies have evaluated about proper risk models to be used for valuing risk and which is the most accurate. Since accuracy of risk estimation depends on model used, several risk models are then developed and tested for appropriateness. However, Angelidis and Degiannakis (2005), for example, suggested that there was not a specific model that can accurately estimate VaR for all financial markets and trading positions.

Although Value-at-Risk (VaR) seems to be a standard tool for risk management, it fails to capture extreme event which is unlikely but possible to occur. A stress test is then developed to overcome the problem. While VaR's objective is to quantify potential losses under normal market condition, a stress testing's objective is to evaluate extreme losses that rarely but possible to occur. According to historical data, VaR is unable to describe abrupt changes in market circumstances "since such changes are, by definition, atypical" (Lopez (2005)). Then, a stress test is usually used as a supplement to VaR for risk measurement. For example, having been facing deepening recession and financial market turmoil because of a subprime crisis, 19 large bank holding companies are required by the federal bank regulatory agencies to attend the Supervisory Capital Assessment Program (SCAP). The program asks the firms to run stress tests to project their loss, revenue and reserve needed for 2009 and 2010 under baseline and adverse scenarios since only historical data in not sufficient for estimating loss under current volatile period. However,rather than a risk quantifying measurement with a probability statement like VaR, a stress testing is a non-statistical risk measurement (Jorion (2007)). Therefore, stress testing although useful and also necessary and required by Basel II, it is difficult in implementation since the results are presented without probability. Traditional stress testing required knowledge and understanding about which possible scenarios could affect losses. Hence, it is possible that some scenarios could be ignored or added without necessary if the one who running a stress test is not thoroughly understand the firm and market conditions. In addition, working with stress test, risk managers have to tradeoff between scenario realism and comprehensibility. That is the more developed scenarios, the more difficulty for result interpretation. (Lopez (2005))

In this study, we will investigate a stress testing methodology based on market risk model developed by Alexander and Sheedy (2008) in the context of Thai financial markets. The stress testing methodology could be useful and is an alternative to traditional methodology. According to Alexander and Sheedy (2008), the methodology is superior to the traditional method in that it able to link stress tests to a targeted probability, provides greater statistical reliability, able to examine market response following a shock event, and able to evaluate alternative hedging strategies along with the impact of limits or margins on expected losses and funding liquidity. The objective of this study is to identify the most suitable risk models for conducting a stress test in the context of a risk model. The stress testing methodology is conducted on foreign exchange market of long and short positions in THB/USD from July 2, 1997 to December 30, 2008, and stock market of SET50 index from August 16, 1995 to December 30, 2008.

The paper is organized as follows: Section II provides reviews of previous studies related to VaR and stress test. Detailed methodology of this study is explained in section III while empirical results and conclusion are shown in section IV and V respectively.

II. Literature Review

Value-at-Risk (VaR) has increasingly been an essential tool for risk management, especially for financial institutions. In general, VaR is defined as the worst expected losses over a target horizon for a given confidence level. Specifically, VaR is the figure that relates amount of potential losses of a portfolio to probability of its occurrence (Stambaugh (1996)). In measuring VaR, there are three main approaches; analytical approach or variance-covariance approach, historical simulation approach, and Monte Carlo simulation approach. Each approach has its own merits and drawbacks. However, all approaches share the same basic principal that the recent past market behavior is a good and unbiased indicator for the market behavior in the near future (Stambaugh (1996)). Since such relevance is decayed with time, it is preferred not to use data that is deep into the past, or to use data weighting scheme that reflect varying importance of data such as exponentially weighting moving average (EWMA) method. In addition, such the relevance contributes to the use of conditional volatility models such as several kinds of GARCH model and several studies exhibit the superior of conditional model to the unconditional (for example in Alexander and Sheedy (2008); Nilla-or (2008))

According to VaR calculation, estimated VaR is based on the assumed probability distribution of expected returns. There are debates about which distribution should be used for the estimation. Assumption that return distribution is normally distributed is proven to be invalid in several studies. The distribution in fact exhibits fat tails. That is extreme movement, either up or down, is more likely to happen rather than suggested by the normal distribution, and as a result losses estimated by normal distribution assumption is underestimate (Stambaugh (1996); Tan and Chan (2003)). Some may abandon this problem by using historical simulation which let the history movement reveals the distribution itself. However, an appropriate sample size for the simulation is arguable that affecting the precision of VaR estimated (Stambaugh (1996); Angelidis and Degiannakis (2005); Alexander and Sheedy (2008)). One popular way to incorporate fat tails is to use a Student-*t* distribution (e.g. in

Alexander and Sheedy (2008); Ku (2008)). However, Tan and Chan (2003) applied StressVaR and StressVaR-x models with portfolio of long position in eight Asian currencies during 1992-1999 and found that despite evidence of fat-tailed return distribution, the StressVaR-x model which assumes Student-*t* distribution only slightly outperformed the StressVaR model which assumes normality at the 99% confidence level. They then suggested that normality assumption was still appropriate for stress testing. The Extreme Value Theory (EVT) which focuses on the tails behaviors of return distribution has later been developed. It is superior to traditional VaR since the method does not assume a particular model for return and investigates only the tails of the return distribution (Longin (2000); Nilla-or (2008)). The EVT framework, however, is criticized for its complexity and only slightly outperforms or is only as good as other simple VaR methods (Alexander and Sheedy (2008)). Wongchotiwat (2005) studied the Peak Over Threshold (POT) model in estimating VaR based on the EVT in SET index and THB/USD exchange rate and found that the EVT-based approach and historical simulation were both well protective of risk at very high confidence level. Nilla-or (2008) estimated VaR and expected shortfall in ten East Asian market indices under conditional EVT framework. The result showed that while the conditional EVT model provided better one-day estimates than model with normality assumption, it was not trivially different from filtered historical simulation. In addition, with the well-designed VaR model, the EVT could even underperform the model. Srisopitsawat (2003) proposed a trimodal distribution of returns which combined normal distribution and stochastic jumps in VaR analysis of S&P500 index from 1969-2002. When comparing the trimodal distribution with alternative models including normal distribution, the Student-*t* distribution, the EVT, and the bimodal distribution, the result suggested that the trimodal distribution outperformed all other models.

Although Value at Risk (VaR) has widely used as a standard risk-management tool, it cannot capture all possible outcomes. Since VaR considers only likely losses, there still some extreme losses that unlikely but possible to occur beyond the VaR. Although some severe situations like the Black Monday (1987), Asian financial crisis (1997), subprime crisis (2008), etc., infrequently happen, one cannot ignore them since when the situations do occur, loss incurred usually unimaginable. Stress testing is then developed to identify such extreme but probable loss. The standard methodology for stress testing has not yet been emerged. However, there is a consensus that the assumptions under the VaR methodology become invalid and historical correlation structure tends to breakdown when the portfolio is under stress. Therefore, subjective ‘what if’ scenarios have become key inputs for calculating losses when performing stress test (Tan and Chan (2003)). Stress test is then not associated with a probability statement like a VaR and as a result difficult for interpretation and implementation. In addition, since the method is highly subjective, several scenarios might be unreasonable or even be ignored resulting in inappropriate losses and could lead to improper policy (Jorion (2007); Berkowitz (2000)).

Several studies about VaR try to evaluate the performance of VaR models in order to find the best VaR measurement. Angelidis and Degiannakis (2005) investigated accuracy of several VaR models, including a set of ARCH models, historical and filtered historical simulations, and variance-covariance method, in predicting one-day-ahead VaR in stock exchanges, commodities, and exchange rate both in long and short positions. The result suggested that there was not a specific model that can accurately estimate the VaR number for all financial markets and trading positions. Backtesting procedure is usually used for assessing model performances. Tan and Chan (2003) used the proportion of failure test (PF test) which expressed the optimal number of failures allowed for a given of sample size and probability of failure to evaluate performance of StressVaR and StressVaR-x models. Angelidis and Degiannakis (2005) employed a two-stage procedure to investigate forecasting power of each VaR measurement. The first stage was to use the Kupiec (1995) unconditional coverage test and the Christoffersen (1998) conditional coverage test for testing statistical accuracy of the models. The Lopez (1999) loss function was then used to compare the best-performing model. The second stage was to examine whether the differences between models were statistically significant using Diebold-Mariano *t*-statistic.

In this study, we will estimate VaR of Thai Baht exchange rates against US Dollar using several kinds of risk models focusing primarily on conditional risk models. Using Alexander and Sheedy (2008) not only allows us to evaluate risk models more thoroughly with several steps of evaluation, but also provides new stress testing framework for Thai data. In addition, while Alexander and Sheedy (2008) only presented the study on foreign exchange market, this study will investigate in both foreign exchange and stock markets.

III. Methodology

In this section, data and detailed methodology are described. SET50 index and USD/THB currency pair are the data of interest. The methodology used in this study follows Alexander and Sheedy (2008).

3.1 Data

Daily exchange rates of Thai Baht in terms of US Dollar (THB/USD) retrieving from Datastream, and daily closing SET50 index retrieving from SET SMART are used in this study. The exchange rate data spans from July 2, 1997 to December 30, 2008, while SET50 index data spans from August 16, 1995 to December 30, 2008. That is we have 2,823 trading days of exchange rate data and 3,283 trading days of SET50 index data. For exchange rate, we consider the portfolio of both long and short positions.

3.1.1 Descriptive Statistics of Daily Returns

Daily returns of exchange rates and SET50 index are calculated using natural logarithm of daily price.

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

where P_t is the daily reported price of exchange rate or SET50 index on day t, and R_t is the return on exchange rate or SET50 index on day t.

Each returns series will be analyzed for its distribution. A normal distribution is not appropriate if there exists a fat-tailed. Jarque-Bera test is used for a normality hypothesis testing.

$$JB = T\left(\frac{\hat{\gamma}^2}{6} + \frac{(\hat{\delta}-3)^2}{24}\right) \sim \chi^2 \tag{2}$$

where T is the number of observations, $\hat{\gamma}$ is the sample skewness, and $\hat{\delta}$ is the kurtosis of the series. For large sample sizes, the test statistic has a chi-square distribution with two degrees of freedom. A Jarque-Bera tests the null hypothesis that the sample comes from a normal distribution against the alternative that it does not come from a normal distribution.

3.2 Methodology

The methodology described follow is from Alexander and Sheedy (2008). It can be separated into 4 main parts which are estimation of VaR and ETL, appropriate risk model selection, stress testing, and model-based stress test evaluation. Details of the methodology are as followed;

3.2.1 Value-at-Risk (VaR) and Expected Tail Loss (ETL) estimations

The process starts with estimation of VaR and ETL for each risk model. There are 4 risk models in this study: unconditional normal, conditional normal, conditional Student's *t*, and conditional empirical risk models. The unconditional risk model is used for the purpose of benchmarking and because it is widely used in financial industry. However, we expect better estimations of VaR and ETL from the conditional model since it is beneficial in capturing a volatility clustering that is potentially significant in a stressful market (Alexander and Sheedy (2008)). VaR and ETL are estimated at 99.0% confidence level for a risk horizon of 1-day. Estimation windows of this study are 250 days. The sample is rolled over daily to keep a sample size constant. Profit and loss of each portfolio is then calculated at the end of risk horizon. The losses that exceed the VaR estimated will be inputs for model backtesting in the next step. The methodology for calculating VaR and ETL for each risk models is described as follow.

3.2.1.1 Unconditional normal risk model

Let ε denotes the difference between actual return and expected return at time t, $\varepsilon = R_t - \overline{R}_t$, and is independently and normally distributed with zero mean and standard deviation σ, $\varepsilon \sim N(0,\sigma^2)$. The VaR and ETL for a horizon of h days at significant level α are:

$$VaR_{h,\alpha} = \Phi^{-1}(\alpha)\sigma_h \tag{3}$$

$$ETL_{h,\alpha} = \alpha^{-1}\varphi(\Phi^{-1}(\alpha))\sigma_h \tag{4}$$

where Φ denotes the standard normal cumulative distribution function, φ denotes the standard normal density function, and $\sigma_h = \sigma\sqrt{h}$. VaR and ETL are represented in absolute value.

3.2.1.2 Conditional normal risk model

The mean adjusted returns are assumed to be conditionally normally distributed with conditional variance following the symmetric GARCH (1,1).

$$\sigma_t^2 = \gamma_1 + \gamma_2\varepsilon_{t-1}^2 + \gamma_3\sigma_{t-1}^2 \tag{5}$$

where $\gamma_1 >> 0, \gamma_2, \gamma_3 > 0$, $\gamma_2 + \gamma_3 < 1$, and ε is independently and normally distributed with zero mean and standard deviation σ, $\varepsilon \sim N(0,\sigma^2)$.

To calculate VaR and ETL, we fit GARCH (1,1) in equation (5) to the data in each estimation window and estimate all parameters. Then we simulate the process 10,000 paths over h-day horizon to find simulated portfolio returns. VaR relative to the mean is calculated according to Jorion (2007), that is

$$VaR(\alpha) = E(R) - Q(R,\alpha) \tag{6}$$

where *E(R)* is the expected portfolio return from the simulated returns and *Q(R,α)* is the return at α quantile. VaR is the absolute portfolio return calculated at the lower *α* percentile for a long position and at the above α percentile for a short position. ETL is calculated corresponding to the VaR. It is the absolute value of the mean of all simulated returns that lie below the VaR for a long position, and above the VaR for a short position.

3.2.1.3 Conditional Student's *t* risk model

The conditional Student's *t* risk model is used in order to capture the conditional excess kurtosis presented in empirical data. The mean adjusted returns are assumed to be conditionally distributed with standardized student's *t* distribution as in equation (7) and conditional variance following the symmetric GARCH (1,1) in equation (5).

$$\varepsilon_t \sigma \left(\frac{v}{v-2} \right)^{\frac{1}{2}} \sim T_v \qquad (7)$$

where T_v is the standardized student's *t* distribution with v degree of freedom, zero mean and unit variance and σ is the standard deviation of the mean-adjusted returns.

To calculate VaR and ETL, we fit GARCH (1,1) in equation (5) to the data in each estimation window and estimate all parameters. Then we simulate the process 10,000 paths over h-day to find simulated portfolio returns. VaR relative to the mean is calculated using equation (6). VaR is the absolute portfolio return calculated at the lower α percentile for a long position and at the above α percentile for a short position. ETL is calculated corresponding to the VaR. It is the absolute value of the mean of all simulated returns that lie below the VaR for a long position, and above the VaR for a short position.

3.2.1.4 Conditional empirical risk model

The empirical risk model using historical simulation is beneficial in that it makes no assumption about the past returns distribution. The distribution then could be asymmetric and results in different VaR and ETL depending on position of a portfolio.

To calculate VaR and ETL, we fit GARCH (1,1) in equation (5) to the data in each estimation window and estimate all parameters. Return in the sample is standardized by dividing each return by the conditional volatility estimating correspondingly to that return. Then we scale all the returns in the sample by multiplying the standardized returns by the conditional volatility applying to the day of VaR and ETL are estimated. The Epanechnikov kernel is then fitted to the scaled returns in order to provide a smoothed distribution of standardized returns. Alexander and Sheedy (2008) used Epanechnikov kernel to fit the data since it can provide the best possible representation of the density of a random variable. We simulate the GARCH model forward with 10,000 paths over h-day risk horizon using innovations that are sampled from the kernel density. VaR relative to the mean is calculated using equation (6). VaR is the absolute portfolio return calculated at the lower α percentile for a long position and at the above α percentile for a short position. ETL is calculated corresponding to the VaR. It is the absolute value of the mean of all simulated returns that lie below the VaR for a long position, and above the VaR for a short position.

3.2.2 Model Selection

Model backtesting is used to verify accuracy of each risk model. We backtest risk models using the Kupiec test for unconditional coverage, the Christoffersen test for conditional coverage, and the McNeil and Frey ETL test.

3.2.2.1 Test for unconditional coverage

The test for unconditional coverage is a likelihood ratio (LR) test of the form:

$$LR = \frac{\pi_{\exp}^{n_1}(1-\pi_{\exp})^{n_0}}{\pi_{obs}^{n_1}(1-\pi_{obs})^{n_0}} \tag{8}$$

where $-2\ln LR$ is asymptotically distributed chi-square with one degree of freedom, $-2\ln LR \sim \chi_1^2$.

π_{exp} is the expected proportion of returns that lie in the prescribed interval of the distribution which in this study is α

π_{obs} is the observed proportion of returns that lie in the prescribed interval of the distribution calculated by dividing is the number of returns that lie inside the interval by the total number of VaR estimates

n_1 is the number of returns that lie inside the interval (the number of violations)

n_0 is the number of returns that lie outside the interval (the number of good returns).

The null hypothesis is:

H_0: the actual number of violations is equal to the expected number of violations

At 95% confidence level, we reject a null hypothesis with p-value of less than 5%.

3.2.2.2 Test for conditional coverage

The test for conditional coverage is

$$LR = \frac{\pi_{\exp}^{n_1}(1-\pi_{\exp})^{n_0}}{\pi_{01}^{n_{01}}(1-\pi_{01})^{n_{00}}\pi_{11}^{n_{11}}(1-\pi_{11})^{n_{10}}} \tag{9}$$

where $-2\ln LR$ is asymptotically distributed chi-square with one degree of freedom, $-2\ln LR \sim \chi_1^2$.

$$\pi_{01} = \frac{n_{01}}{n_{00}+n_{01}} \tag{10}$$

$$\pi_{11} = \frac{n_{11}}{n_{10}+n_{11}} \tag{11}$$

where n_1 is the number of returns that lie inside the interval (the number of violations)

n_0 is the number of returns that lie outside the interval (the number of good returns).

n_{10} is the number of times a violation is followed by a good return

n_{11} is the number of times a violation is followed by another violation

n_{01} is the number of times a good return is followed by a violation and

n_{00} is the number of times a good return is followed by another good return.

π_{exp} is the expected proportion of returns that lie in the prescribed interval of the distribution which in this study is α

π_{01} is the proportion of exceedances, give that the last return was a good return

π_{11} is the proportion of exceedances, given that the last return was an exceedance.

The null hypothesis is:

H_0: Violations are spread evenly over time (that is the violation is not clustered)

At 95% confidence level, we reject a null hypothesis with p-value of less than 5%

3.2.2.3 ETL test

The ETL test starts by finding the return that exceed the VaR estimated. Then we compute standardized exceedance residuals as follow;

$$r = \frac{(R_{t+h} - ETL_{h,\alpha})}{\hat{\sigma}_{t+h}} \qquad \text{if } R_{t+h} < -VaR_{h,\alpha} \text{ and}$$

$$r = 0 \qquad \text{otherwise} \tag{12}$$

where R_{t+h} is the actual return on the day that $VaR_{h,\alpha}$ and $ETL_{h,\alpha}$ are estimated

$ETL_{h,\alpha}$ is the ETL estimated for a holding period of h-day at significant level α

$VaR_{h,\alpha}$ is the VaR estimated for a holding period of h-day at significant level α

$\hat{\sigma}_{t+h}$ is the estimated standard deviation applying to the day that $VaR_{h,\alpha}$ and $ETL_{h,\alpha}$ are estimated.

The standardized exceedance residuals then use to find t-statistic where the distribution of the test statistic is

$$t = \frac{\bar{r}}{\hat{\sigma}_r} \tag{13}$$

where $\bar{r}$ is the mean of standardized exceedance residuals

$\hat{\sigma}_r$ is the standard deviation of the standardized exceedance residuals

To test for the null hypothesis, we follow the standard bootstrap simulation introduced by Efron and Tibshirani (1993, pp.224-7).

The null hypothesis is

H_0: The standardized exceedance residuals have zero mean, or equivalently ETL does not consistently understate the true potential for losses beyond the VaR.

At 95% confidence level, we reject a null hypothesis with p-value of less than 5%.

3.2.3 Stress Testing Methodology

3.2.3.1 Identify initial shock

Initial shock event, according to Alexander and Sheedy (2008), is "a large gap or discontinuity in prices typically caused by important unanticipated information entering the market". Refer to VaR_{α}, it estimates loss that should not exceed α% of case. Therefore, the model based stress test interprets α as the probability of a market shock. The size of shock is $-VaR_{1,\alpha}$ for a long position, and is $VaR_{1,(1-\alpha)}$ for a short position. In this study, we estimate initial shocks of α=0.01, α=0.005, and α=0.001, corresponding to a 99% , 99.5%, and 99.9% confidence level that loss will not be exceeded over one day.

The initial shock, ε^*, for each risk model is calculated as follow.

3.2.3.1.1 Normal distribution

Under the normal distribution, the initial shock is

$$\varepsilon^* = \Phi^{-1}(\alpha)\sigma 1 \tag{14}$$

where Φ denotes the standard normal cumulative distribution function, and σ is the estimated standard deviation. 1 is an indicator variable taking the value -1 if we are long the portfolio and 1 otherwise.

3.2.3.1.2 Student's *t* approach

Under the Student's *t* distribution, the initial shock is

$$\varepsilon^* = t_v^{-1}(\alpha)\left(\frac{v-2}{v}\right)^{\frac{1}{2}} \bar{\sigma}_t 1 \tag{15}$$

where $\bar{\sigma}_t$ is the equally weighted sample standard deviation using all available data up to the time of estimation, representing long term volatility. v is the degrees of freedom estimated using maximum likelihood estimation. t_v^{-1} denotes the standard Student's t cumulative distribution function with v degrees of freedom. 1 is an indicator variable taking the value -1 if we are long the portfolio and 1 otherwise.

3.2.3.1.3 Empirical distribution

Under the empirical approach the initial shock ε* for the long asset position is simply the α percentile of the empirical distribution using a large sample of data. For the short position, the initial shock is the 1-α percentile of the distribution.

3.2.3.2 Evaluate after-shock effect

Shock event could lead to some or all of the following: further large moves in the same market, large moves in other markets and higher correlations between markets, increased implied volatility in option markets and reduced market liquidity. (Alexander and Sheedy (2008)) For evaluating after-shock effect, we investigate a time period of h days. Initial shock occurs at time T and portfolio returns are assessed for h-1 days after the shock. Standard deviation is set equal to the long-term value at the first day, the day of the initial shock. At time T+1, variance will increase significantly in response to the extreme initial shock in the previous day. For the subsequent days, innovations are drawn from the chosen distribution, i.e. normal, Student's *t*, and empirical distribution, and scaled to the appropriate conditional variance. We apply (4) to determine the variance on subsequent days along the period of the stress test. The variance on the subsequent day for i=1,…,h-1 is defined as:

$$\hat{\sigma}^2_{T+i+1} = \hat{\gamma}_1 + \hat{\gamma}_2 \varepsilon^2_{T+i} + \hat{\gamma}_3 \hat{\sigma}^2_{T+i} \quad (16)$$

Monte Carlo simulation is used to simulate possible returns after the initial shock. We simulate 10,000 paths of returns. Daily returns along each path are then aggregated. Portfolio is assumed to be held constantly along the stress test duration. The stress loss for a long position is -1 times the lower ϱ percentile of the simulated h-day returns when returns are ranked from highest to lowest. For a short position, we first multiply the return by -1 and the stress loss is calculated using the same method.

3.2.4 Model based stress testing evaluation

The results from the stress test will be used to evaluate the effectiveness of the model-based stress test. In this study, there are 4 aspects of evaluation;

- Comparing stress test results by risk model: Since different risk model can provide different predicted stress loss, in order to assess ability of each risk model in forecasting stress loss, we find the worst historical loss over h-day horizon to compare with the stress loss provided by each risk model. That is the risk model that can provide the stress loss beyond the worst historical loss should be preferred.
- Comparing traditional stress tests with model based stress tests: The familiar traditional stress test model usually assumes unconditional normal distribution. We will compare stress test results of unconditional normal model with the other conditional risk models whether the conditional provide better stress loss results.
- Comparing stress loss with VaR-based regulatory capital: We test whether the result from the model based stress test can provide good implications for risk capital. That is whether the capital requirement estimates could sufficiently cover the loss generated from model based stress test. The regulatory capital is calculate as 3 time of the estimated VaR at 99% confidence level for 10-day holding period, $3VaR_{0.01,10\text{-}day}$.
- Model-based stress test overtime: Since the VaR estimated by the GARCH model can increase suddenly and dramatically following a shock while the capital is not possible to be raised within a short period, it is necessary to assess the stability of the model-based stress test over time. Therefore, we repeat a stress test quarterly after 10 years of data. That is we use 10 year of data, i.e., August 1995 to August 2005 for SET50 index, and July 1997 to July 2007 for USD/THB currency pair, to estimate long term volatility, the reaction term of the GARCH equation (γ_2), and other necessary parameters of each model. The stress loss is estimated quarterly using all available data since the first data to the estimation point. Then we evaluate for the stability of the model-based stress test.

IV. Empirical Results

The empirical results are separated into 3 parts. In the first part we will analyse the descriptive statistics of each returns series. The results from the risk model backtesting are provided in the second part. Then each model is put under stress and the results are shown in the last part.

4.1 Descriptive Statistics of Return Series

The return series are analyzed for their basic descriptive statistics in table I. Estimated skewness and kurtosis of the series obviously show that the returns distributions of both SET50 index and THB/USD are non-normal. Returns on SET50 index have a positive skewness implying a larger chance of observing positive returns rather than the negative. Returns on THB/USD on the other hand have a negative skewness indicating a high probability of negative returns to occur. In addition, both series have kurtosis more than 3 while returns on THB/USD have a very high kurtosis meaning that extreme returns occur more often than we can expect from a normal distribution. The Jarque-Bera test of normality also support this fact since we can easily reject a null hypothesis at 95% confident level that the returns have a normal distribution.

[Table I and Figure 1 is here]

4.2 Risk Model Backtesting

Four risk models, namely, unconditional normal, conditional normal, conditional Student's *t*, and conditional empirical risk models, are used to estimate VaR and ETL of each data, i.e., SET50 index, long USD/ short THB, and short USD/ long THB. The estimation window is 250 days. The sample is rolled over daily to keep estimation window constant. For the unconditional normal model, 1-day VaR and ETL are forecasted directly from the recent estimation window. VAR and ETL for the conditional risk models, on the other hand, are estimated by simulating 10,000 paths of possible returns accordingly to the assumed return distribution of each risk model. The estimated VaR and ETL are used as input for model backtesting in order to find which risk model can provide good estimates of VaR and ETL. The Kupiec (1995) test for unconditional coverage of VaR, Christofferson (1998) test for conditional coverage of VaR, and McNeil and Frey (2000) test of ETL are used for backtesting all risk models. Hypothesis is tested at 95% confident level. The result is shown in table II.

[Table II is here]

Table II provides backtesting results of VaR and ETL at 99% confident level. In every case, we cannot reject a null hypothesis at 95% confidence level for the conditional Student's *t* risk model that the actual number of violations is equal to the expected number of violations, a null hypothesis that violations are spread evenly over time, and a null hypothesis that the ETL does not consistently understate the true potential for losses beyond the VaR. For the conditional empirical risk model, we cannot reject a null hypothesis regarding unconditional coverage for 2 out of 3 cases. In addition, the risk model based on conditional empirical distribution can provide a good estimate of ETL since all of the cases we fail to reject a null hypothesis that the ETL does not consistently understate the true potential for losses beyond the VaR. Only one of all cases that we can reject the null hypotheses of the unconditional and conditional coverage, and ETL test for the conditional normal risk model. As expected, the unconditional normal risk model underperforms all conditional risk models since we can reject almost all null hypotheses at 95% confident for all cases. The VaR and ETL estimated by unconditional risk model understate the actual losses, and cannot capture volatility clustering which are the two key characteristics of accurate risk model according to Alexander and Sheedy (2008).

Backtesting result of USD/THB foreign exchange rate shows a similarity with the results of risk model backtesting of major currencies tested by Alexander and Sheedy (2008). That is for VaR and ETL estimated at 99% confidence level, we cannot reject all null hypotheses of both long and short positions of the conditional Student's *t* risk model. However, while Alexander and Sheedy (2008) could not reject for all cases of VaR and ETL estimated at 99%

confidence level the 3 null hypotheses for the conditional empirical risk model, we reject the null hypotheses regarding unconditional and conditional coverage for a long position in USD/THB.

4.3 Model-based Stress Tests

Risk model backtesting have shown that unconditional normal risk models, both for SET50 index and USD/THB returns, cannot provide good estimates of VaR and ETL calculated at 99% confidence since we can reject almost all the null hypotheses. Therefore, it is more appropriate to use conditional risk model to estimate extreme returns rather than the unconditional. Since VaR calculated at 1-α% means that only α% of exceedance from VaR should be occurs, Alexander and Sheedy (2008) then interpret α to the probability of market shock to occur in a given day at a size of $-VaR_{1,\alpha}$. The initial shock for each model is calculated using the approach describe in section III using all available data. Results are shown in Table III.

[Table III is here]

According to Alexander and Sheedy (2008), initial shock event is a large gap or discontinuity in prices. It usually caused by important and unanticipated information. Table III shows the initial shocks estimated by each risk model for several probabilities of exceedance. These initial shocks will be used for stress test instead of the traditional historical or hypothetical methods. In absolute value, the initial shock estimated by Student's *t* risk model is the smallest at $\alpha = 0.01$ and $\alpha = 0.005$, which is equivalent to the 99%, and 99.5% confidence respectively that the loss will not exceed over one day. However, the initial shock for Student's *t* risk model is quite large for a very extreme case, i.e., $\alpha = 0.001$, or equivalent to 99.9% confidence that loss will not be exceeded over one day. On the other hand, the conditional empirical risk model always shows the largest initial shock for every α.

The initial shock assumed to occur on the first day. For the conditional model, this will affect variance of the following day and hence the returns. The forecasted returns after the shock are simulated with 10,000 paths and are aggregated along the holding period of each path to estimate the stress loss at 99% confidence level. Stress Loss refers to -1 times the stress test outcome expressed as a percentage of initial portfolio value. The consequence of the shock can be evaluated in several aspects. The following will present stress test result when comparing to each risk model and to traditional stress test method. The stress loss will be compared to VaR-based regulatory capital. We will also evaluate the stress test result over time to assess stability of the model-based stress test.

4.3.1 Comparing stress test by risk model

We compare stress test results of each risk model for an initial shock calculated at α=0.01, α =0.005, α =0.001, and a holding period of 3-day and 10-day. We also calculate the worst historical loss over 3-day and 10-day to compare with the stress loss estimates. The portfolio is assumed to be held constantly over the holding period. Table IV shows the stress test results.

[Table IV is here]

Table IV shows that for every risk model, data, and holding period, α of 0.01 and 0.005 cannot provide stress loss that large enough to cover the worst historical loss. Since the worst historical loss is an extreme case, α of 0.001 might be more appropriate to be used in order to provide proper size of stress loss. For SET50 index, all conditional risk models can provide stress losses that are large enough to cover the worst historical loss over 10-day holding period. That is we are 99% confident that when stress event occurs, the loss over 10 days will no greater than 32.26%, 38.24%, and 34.76% for conditional normal, conditional Student's *t*, and conditional empirical models respectively, while the worst historical loss over 10 days is only 30.13%. However, for 3-day holding period, only conditional Student's *t* and conditional empirical risk models can provide stress loss that covers the worst historical loss. The models predict that the loss over 3 days will no greater than 22.83% and 21.48% for each model respectively, while the worst historical loss over 3 days is 20.62%. The worst 3-day and 10-day historical loss occurred in October 2008 where subprime crisis is the cause of stock markets crash around the world.

For USD/THB, both long and short positions, only conditional Student's *t* risk model can provide stress loss that is larger than the worst historical loss for every holding period at initial shock $\alpha=0.001$. For example, we are 99% confident that when stress event occurs, the loss over 3 days and 10 days of short position in USD/THB will no greater than 14.41%, and 30.95% while the worst historical losses are 10.17% and 17.66% respectively. The worst historical loss over 3-day holding period is also in the range predicted by the conditional empirical risk model for a short position in USD/THB. The worst historical loss over 3-day and 10-day occurred during a greatly volatile period of December 1997 to February 1998 where Thai Baht against US Dollar hits the highest rate in 13 January 1998 at the rate of 55.88 Bath per US Dollar.

4.3.2 Comparing traditional stress test with model based stress test

When comparing a widely use unconditional normal risk model with the conditional risk models, the results in table IV is obvious that the stress loss estimated by the unconditional risk model is too small when comparing with the worst historical loss. Although not all conditional risk models can provide the stress loss that is sufficient to cover the worst historical loss, the stress loss estimated by the unconditional model is very far from the extreme loss. For example, in the case of SET50 index, the unconditional risk model forecast a 99% stress loss at $\alpha=0.001$ for 10 days at 21.22%, while the worst historical loss over 10-day is 30.13%. The conditional models, on the other hand, estimate stress losses in the range of 32.26%-38.24% which are sufficient to cover the worst historical loss. Therefore, the conditional risk model is preferred for model based stress test in the case of SET50 index and long and short positions in THB/USD currency pair.

4.3.3 Comparing stress loss with VaR-based regulatory capital

The VaR-based regulatory capital is estimated according to Alexander and Sheedy (2008) using $3VaR_{0.01,\ 10\text{-day}}$. Figure 2-4 show comparisons of VaR-based regulatory capital and stress loss for conditional risk model of SET50 index, long USD/ short THB, and short USD/ long THB, respectively.

[Figure 2 is here]

Figure 2 shows a comparison of regulatory capital for SET50 index represented by a horizontal solid line, and 99% confident stress loss for various initial shocks. For a holding period of 20 days, the VaR-based regulatory capital is sufficient to cover the stress loss of initial shock at α=0.01 and α =0.005. However, for an extreme initial shock, α =0.001, the stress loss would exceed the regulatory capital in some day depending on risk model. That is the stress losses will exceed the regulatory capital if holding period is more than 14, 13, and 18 days for conditional normal, conditional Student's *t*, and conditional empirical risk model respectively.

[Figure 3 is here]

For a long position in USD/THB, the result is different. Only a conditional empirical risk model could provide VaR-based regulatory capital that is sufficient to cover the stress loss of initial shock at α =0.01 and α =0.005 along 20 days. For initial shock at α =0.001, the stress losses will exceed the regulatory capital if holding period is more than 5 days, and 2 days for conditional normal and conditional empirical risk model. The stress losses provided by conditional Student's *t* risk model exceed the VaR-based regulatory capital since the first day because of larger range of stress losses than other conditional models. The results for a short position in USD/THB are very similar to that of the long position and are shown in figure 4.

[Figure 4 is here]

In both long and short positions in USD/THB, while the Student's *t* risk is the only risk model that can provide sufficient size of stress losses to cover the worst historical loss over 3-day and 10-day, the VaR-based regulatory capital calculate at $3\text{VaR}_{0.01,10\text{-day}}$ is not sufficient and need to be increased.

4.3.4 Model-based stress test overtime

According to Alexander and Sheedy (2008), some institutions avoid using conditional risk models such as GARCH-based VaR because the VaR estimated by the model can increase suddenly and dramatically following a shock. The capital, on the other hand is not possible to be raised within a short period. Therefore, it is necessary to assess the stability of the model-based stress test over time. We repeat a stress test quarterly after 10 years of data. While Alexander and Sheedy (2008) recommended using a very long series of data of at least 20 year, we cannot do that for both SET50 index and floating USD/THB currency because data is only available since 1995 and 1997 respectively. This could be a cause of unstable stress test result over time. For SET50 index, long term volatilities for every risk models show a gradual downtrend while GARCH coefficients show a slowly declining trend in the first 6 quarters then increase and remain quite stable. The stress loss provided by conditional risk models also exhibit a downward trend and then increase as the same way as the GARCH coefficients. However, only the conditional normal risk model shows a stable trend after that. Figure 5 shows the 99% stress loss of conditional risk model for an initial shock of α=0.001.

[Figure 5 is here]

For long and short position in USD/THB, figure 6 and 7 show the 99% stress loss of conditional risk model for an initial shock of α=0.001. Estimated long term volatilities are quite stable for conditional Student's *t* and conditional empirical risk models, while there is a sign of gradual decline in conditional normal model. GARCH coefficients are very similar among models that the coefficients exhibit a bit of fluctuation in the first 3 quarters then remain quite stable. The stress losses provided by each risk model for a long position are quite stable and show a similar trend with the long term volatilities and the GARCH coefficients. Stress losses of a long position in USD/THB over time for each risk model are shown in figure 6.

[Figure 6 is here]

For a short position, similar results are presented in figure 7. Estimated stress losses of the conditional normal and conditional Student's *t* risk models are quite stable and show a similar trend with the long term volatilities and the GARCH coefficients. Although the conditional empirical model shows a more fluctuation of stress losses than the others, the estimated stress losses seems to converge into a quite stable trend.

[Figure 7 is here]

However, stress testing over time at larger α, such as α=0.01, provides quite stable stress loss results for both long and short positions in USD/THB, and SET50 index. The result is shown in the appendix in figure A-1 to A-3.

V. Conclusion

Financial institutions are required by regulators to have a sufficient capital to cover possible risk. Therefore, a proper risk model is necessary for financial institutions to assess their risks in order to provide information to management team for making strategic decision, and to prepare appropriate holding capital against the risks.

This study follows Alexander and Sheedy (2008) of estimating stress test based on market risk model to investigate Thai financial market, i.e., SET50 index, and long and short positions in USD/THB currency pair. There are 4 risk models in this study which are unconditional normal, conditional normal, conditional Student's *t*, and conditional empirical risk models. Starting with risk models backtesting in order to evaluate ability of VaR and ETL forecasting, the results shows that, similar to several studies, the unconditional risk model is inferior to other conditional risk models when estimate VaR and ETL for SET50 index and long and short positions in USD/THB since we can easily reject almost all null hypotheses of all tests in every cases. Among conditional risk models, the conditional Student's *t* risk model seems to be preferred than the others because we cannot reject a null hypothesis at 95% confidence level that the actual number of violations is equal to the expected number of violations, a null hypothesis that violations are spread evenly over time, and a null hypothesis that the ETL does not consistently understate the true potential for losses beyond the VaR for all cases.

Stress test results also support the use of conditional risk model for estimating losses from investing in SET50 index and entering long and short positions in USD/THB. The worst historical losses far exceed the stress loss predicted by the unconditional risk model. Then it is inappropriate to use the unconditional risk model. When comparing stress test results among conditional risk models, the Student's *t* risk model outperforms the others. It is the only risk model that can estimate stress losses that more than the worst historical losses over 3-day and 10-day for SET50 index, and long and short positions in USD/THB currency pair cases. However, while the conditional Student's *t* risk model provides the best estimate of stress loss among other risk models, the stress losses are much larger than the VaR-based regulatory capital. This may weaken the use of stress testing framework based on market risk model with Thai financial data, especially USD/THB currency pair.

In order to support the use of model based stress test, we also evaluate stress test result over time for its stability. While it is difficult for financial institutions to raise funds suddenly after a shock, the stress loss estimated from risk model then should be quite stable. The results show that, using 10 years of data and $\alpha=0.001$ initial shock, the estimated stress losses for SET50 index and long and short positions in USD/THB currency pair are quite stable over time although they show a bit of fluctuation in conditional empirical model. More stable results can be retrieved from a less extreme shock such as at $\alpha=0.01$.

The possible reason for stability problem could be because of short data series. While Alexander and Sheedy (2008) recommended using a very long series of data of at least 20 years, we cannot do that for both SET50 index and floating USD/THB currency because data is only available since 1995 and 1997 respectively. In addition, as stated by Alexander and Sheedy (2008) that even long series of data is available, a recently deregulated market or a market that is likely to be deregulated in the near future will have a problem with the model based stress test because of irrelevant data. For foreign exchange market, Thailand has just let Thai Baht to be float against other currencies in 1997. Therefore, the model based stress test for SET50 index and foreign currencies could be more appropriate to use if we have longer data series or remove irrelevant data from period of study. In addition, adjusting for VaR-based regulatory capital is also required.

Nevertheless, it is important to note that estimating power of the risk model is subject to assumptions and samples. Therefore, results from the model based stress test on SET50 index or THB/USD currency pair could be vary by assuming other returns distributions, changing sample period, deciding different α, or providing other assumptions. For example, Alexander and Sheedy (2008) used a two-component conditional normal mixture risk model for estimating risk of major currencies. Other type of GARCH models could provide better estimates of conditional variance and hence the estimated losses. The model could also be benefit from smaller or longer sample period. Sizes of estimation window might matter as having been suggested by Alexander and Sheedy that long estimation windows is preferred. Different α offers different probabilities of shocks to occur which of course affect the stress loss results.

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Table I

Descriptive Statistics of Returns Series

This table provides descriptive statistics of each returns series using all available information. The exchange rate data spans from July 2, 1997 to December 30, 2008, while SET50 index data spans from August 16, 1995 to December 30, 2008. That is we have 2,823 trading days of exchange rate data and 3,283 trading days of SET50 index data. Negative Skewness indicates a long left tail distribution and generates large negative values. Kurtosis of greater than 3 indicates a slow rate of tail decay and provides a likelihood of large values, either positive or negative, to occurs, which is called leptokurtic or fat-tailed. The Jarque-Bera test of normality is performed at 95% confident level.

	SET50	**THB/USD**
Observations	3,282	2,822
Maximum	0.1259	0.0607
Minimum	-0.1723	-0.0644
Median	-0.0011	0.0000
Mean	-0.0004	0.0001
Std. Dev.	0.0207	0.0064
Skewness	0.2676	-0.1552
Kurtosis	9.2262	26.8652
Jarque-Bera	5340.31	66980.94
p-value	0.0010	0.0010

Table II

Backtest Result of Risk Models

This table presents backtesting result of VaR and ETL calculated at 99% confident level over 1- day horizon. We backtest VaR and ETL calculated for 3 data set which are SET50 index, long USD/ short THB, and short USD/ long THB. VaR and ETL are estimated using estimation window of 250 days. The sample is rolled over daily to keep estimation window constant. For the unconditional normal model, 1-day VaR and ETL are forecasted directly from the recent estimation window. VAR and ETL for the conditional risk models, on the other hand, are estimated by simulating 10,000 paths of possible returns accordingly to the assumed return distribution of each risk model. 1) The unconditional coverage VaR tests a null hypothesis that the actual number of violations is equal to the expected number of violations. 2) The conditional coverage VaR tests a null hypothesis that violations are spread evenly over time. 3) The ETL backtest tests a null hypothesis that the ETL does not consistently understate the true potential for losses beyond the VaR. Hypothesis is tested at 95% confident level meaning that a null hypothesis is rejected if p-value is less than 5%.

SET50 index

Innovation Process	Unconditional Coverage VaR[1]	Conditional Coverage VaR[2]	ETL[3]
	***p*-value**	***p*-value**	
Unconditional Model			
Normal	0.29%	0.00%	1.35%
Conditional Model			
Normal	6.43%	5.29%	5.18%
Students' *t*	31.40%	20.44%	26.78%
Empirical	9.21%	0.32%	8.08%

Long USD/ Short THB

Innovation Process	Unconditional Coverage VaR	Conditional Coverage VaR	ETL
	***p*-value**	***p*-value**	
Unconditional Model			
Normal	0.53%	0.04%	0.00%
Conditional Model			
Normal	0.01%	0.01%	0.01%
Students' *t*	23.06%	13.20%	48.09%
Empirical	3.59%	2.90%	63.88%

Long THB/ Short USD

Innovation Process	Unconditional Coverage VaR	Conditional Coverage VaR	ETL
	***p*-value**	***p*-value**	
Unconditional Model			
Normal	16.69%	0.02%	0.00%
Conditional Model			
Normal	0.89%	0.42%	3.65%
Students' *t*	52.41%	29.64%	22.98%
Empirical	23.06%	13.20%	27.24%

Table III

Initial Shock Calculated by Each Risk Model

The initial shock is the large gap in prices assumed to occur on the first day of stress test. Since VaR calculated at 1-α% means that only α% of exceedance from VaR should be occurs, Alexander and Sheedy (2008) then interpret α to the probability of market shock to occur in a given day at a size of $-VaR_{1,\alpha}$. The initial shock for each model is calculated using all available data.

	Initial Shock	**SET50**	**Long USD/ Short THB**	**Short USD/ Long THB**
α=0.01	Unconditional Normal	-4.82%	-1.48%	1.48%
	Conditional Normal	-4.82%	-1.48%	1.48%
	Conditional Student's *t*	-3.56%	-0.89%	0.89%
	Conditional Empirical	-4.99%	-1.94%	2.08%
α=0.005	Unconditional Normal	-5.34%	-1.64%	1.64%
	Conditional Normal	-5.34%	-1.64%	1.64%
	Conditional Student's *t*	-4.52%	-1.36%	1.36%
	Conditional Empirical	-6.74%	-2.68%	2.90%
α=0.001	Unconditional Normal	-6.41%	-1.97%	1.97%
	Conditional Normal	-6.41%	-1.97%	1.97%
	Conditional Student's *t*	-7.69%	-3.57%	3.57%
	Conditional Empirical	-11.43%	-4.60%	4.61%

Table IV
Stress Test Results

The initial shock assumed to occur on the first day. For the conditional model, this will affect variance of the following day and hence the returns. The forecasted returns are simulated with 10,000 paths and are aggregated along the holding period of each path to estimate the stress loss at 99% confidence level. 1) Long-term volatility estimate is sample standard deviation of all daily log returns, expressed on a per annum basis 2) VaR-based regulatory capital is calculate using $3VaR_{0.01,10\text{-day}}$ 3) Stress Loss refers to -1 times the stress test outcome expressed as a percentage of initial portfolio value. Initial shock is set at α. Portfolio is assumed to be held constantly during the period of h-day.

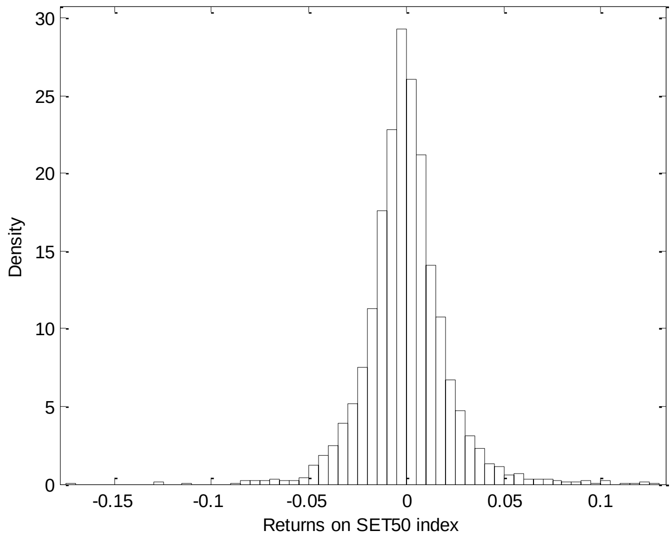
	Unconditional Normal	**Conditional Normal**	**Conditional Students' *t***	**Conditional Empirical**
SET50				
The worst historical loss over 3 days = 20.62%, over 10 days = 30.13%				
Long term volatility estimate[1]	32.78%	32.78%	21.25%	21.25%
VaR-based regulatory capital[2]	45.75%	41.09%	44.18%	46.63%
99% Stress loss[3]:				
H=3, α=0.01	8.28%	10.73%	7.99%	8.61%
H=3, α=0.005	9.37%	12.66%	10.63%	11.37%
H=3, α=0.001	10.98%	17.81%	22.83%	21.48%
H=10, α=0.01	15.37%	19.34%	14.16%	15.63%
H=10, α=0.005	17.51%	22.68%	19.41%	21.54%
H=10, α=0.001	21.22%	32.26%	38.24%	34.76%
Long USD/ Short THB				
The worst historical loss over 3 days = 12.64%, over 10 days = 20.38%				
Long term volatility estimate	10.08%	10.08%	3.39%	3.39%
VaR-based regulatory capital	14.08%	9.91%	10.15%	11.21%
99% Stress loss:				
H=3, α=0.01	2.54%	3.89%	2.39%	3.24%
H=3, α=0.005	2.87%	4.57%	4.35%	4.92%
H=3, α=0.001	3.42%	7.07%	17.95%	11.38%
H=10, α=0.01	4.54%	7.39%	4.44%	5.19%
H=10, α=0.005	5.33%	8.89%	8.04%	7.59%
H=10, α=0.001	6.19%	14.17%	34.64%	16.36%
Short USD/ Long USD				
The worst historical loss over 3 days = 10.17%, over 10 days = 17.66%				
Long term volatility estimate	10.08%	10.08%	3.39%	3.39%
VaR-based regulatory capital	14.08%	10.06%	10.08%	11.66%
99% Stress loss:				
H=3, α=0.01	2.59%	3.91%	2.34%	3.47%
H=3, α=0.005	2.91%	4.71%	4.21%	5.46%
H=3, α=0.001	3.43%	7.10%	18.13%	12.52%
H=10, α=0.01	4.81%	7.60%	4.32%	5.35%
H=10, α=0.005	5.18%	9.44%	7.73%	7.60%
H=10, α=0.001	5.98%	13.73%	34.07%	14.61%

Figure 1

Distributions of Returns Series

This figure provides histograms of returns distribution of each data series. Returns on SET50 index are calculated using closing index data spanning from August 16, 1995 to December 30, 2008. Returns on exchange rate of THB per a unit of USD are calculated from data spanning from July 2, 1997 to December 30, 2008.

SET50 index



THB/USD

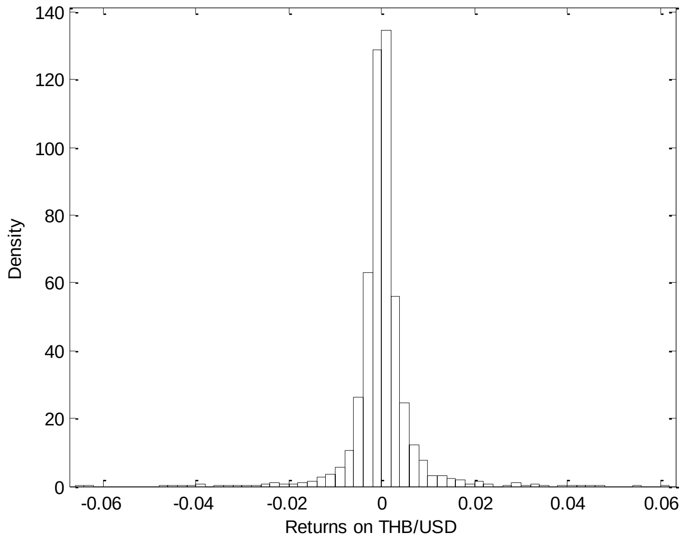
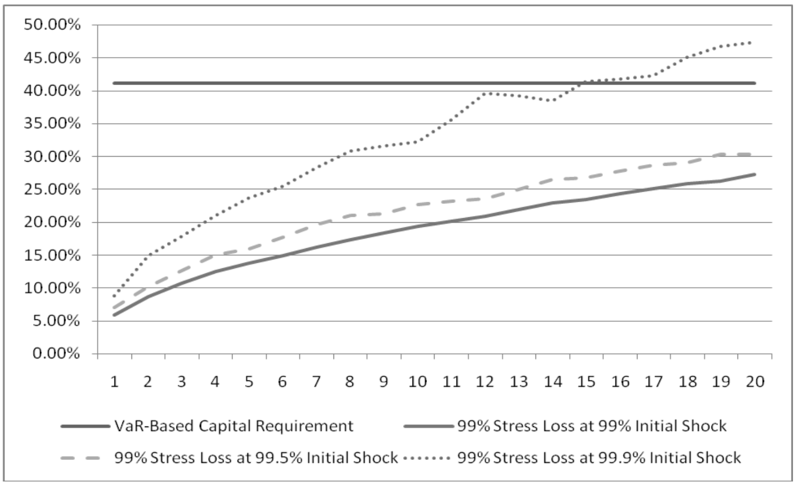


Figure 2

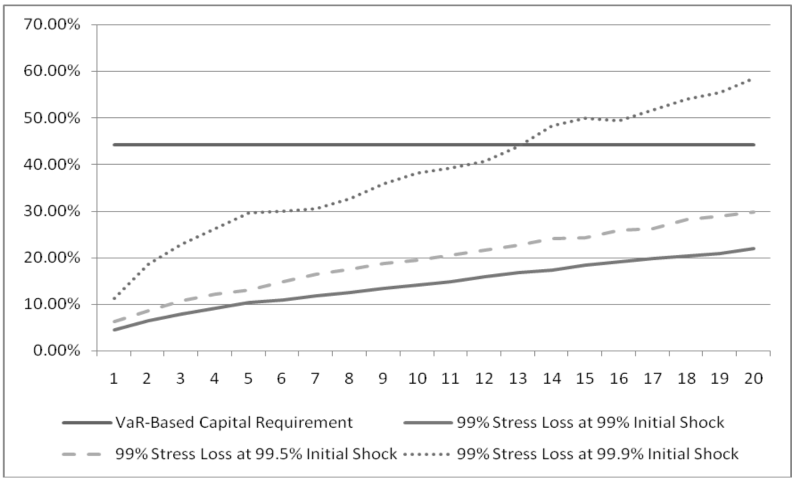
Comparison of Basel I regulatory capital and stress test losses of SET50 index

The figures depict comparison of Basel I regulatory capital calculated according to Alexander and Sheedy (2008) as $3VaR_{0.01,10\text{-day},}$ represented by a horizontal solid line, and 99% confident stress losses for various initial shocks. The horizontal axis represents holing period in days, and the vertical axis represents percentage of portfolio value.

Conditional Normal Risk Model



Conditional Student’s *t* Risk Model



Conditional Empirical Risk Model

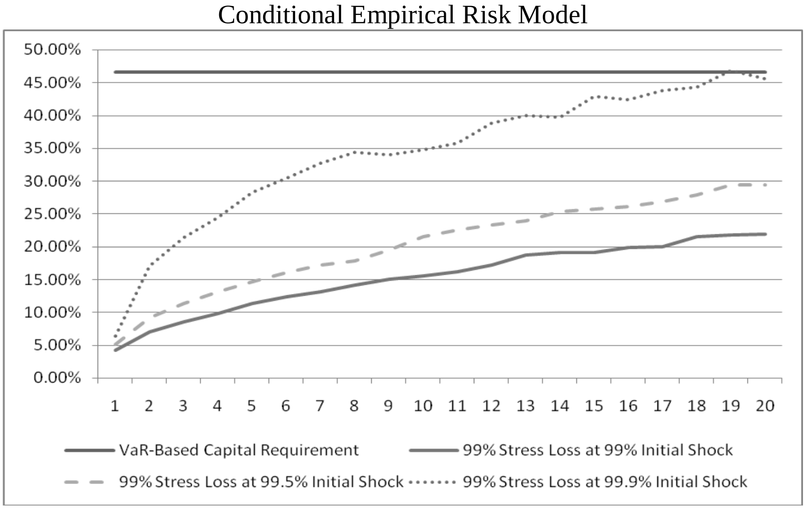
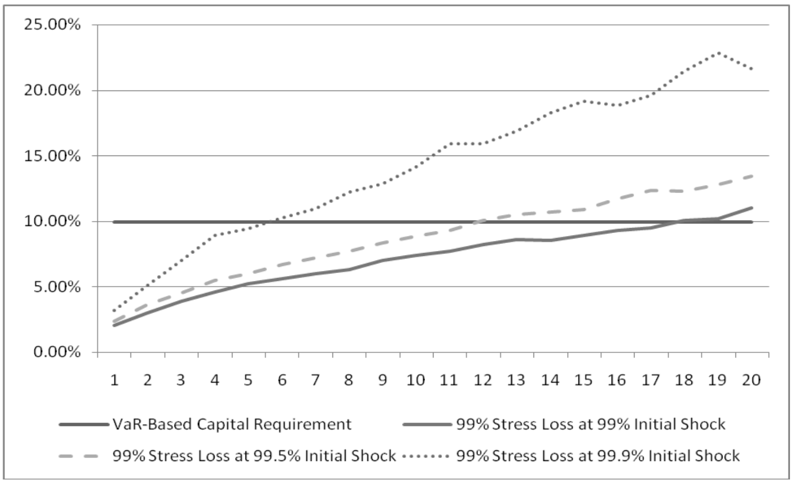


Figure 3

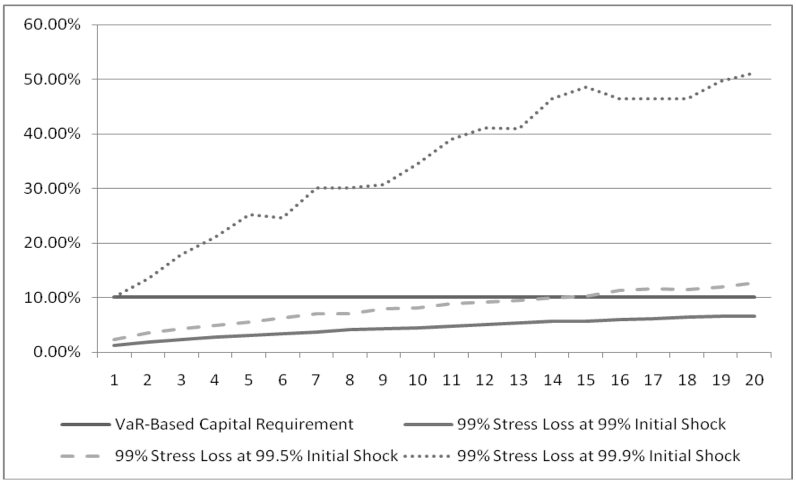
Comparison of Basel I regulatory capital and stress test losses of Long USD/ Short THB

The figures depict comparison of Basel I regulatory capital calculated according to Alexander and Sheedy (2008) as $3VaR_{0.01,10\text{-}day,}$ represented by a horizontal solid line, and 99% confident stress losses for various initial shocks. The horizontal axis represents holing period in days, and the vertical axis represents percentage of portfolio value.

Conditional Normal Risk Model



Conditional Student's *t* Risk Model



Conditional Empirical Risk Model

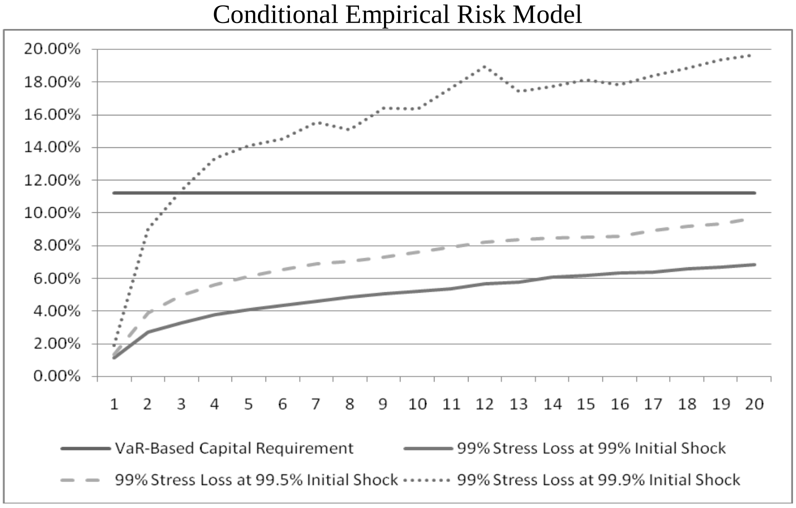
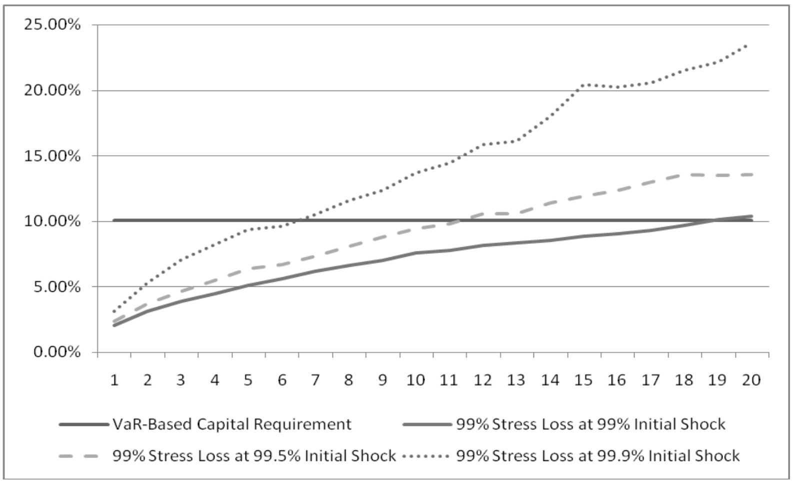


Figure 4

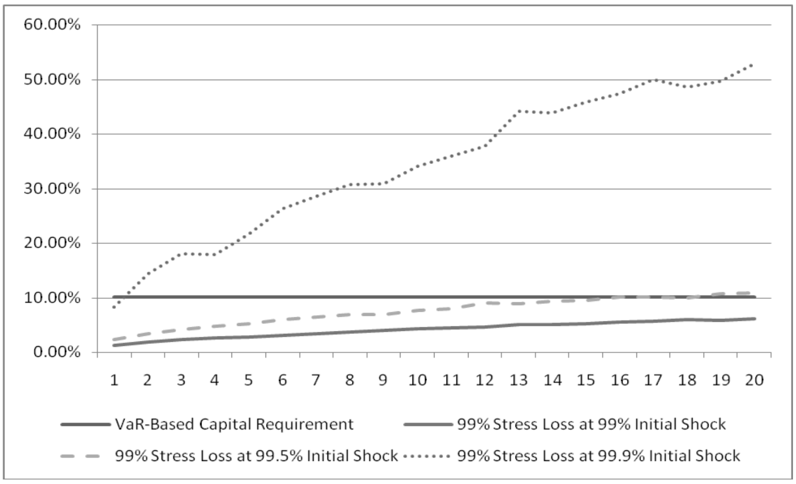
Comparison of Basel I regulatory capital and stress test losses of Short USD/ Long THB

The figures depict comparison of Basel I regulatory capital calculated according to Alexander and Sheedy (2008) as $3VaR_{0.01,10\text{-day}}$, represented by a horizontal solid line, and 99% confident stress losses for various initial shocks. The horizontal axis represents holing period in days, and the vertical axis represents percentage of portfolio value.

Conditional Normal Risk Model



Conditional Student's *t* Risk Model



Conditional Empirical Risk Model

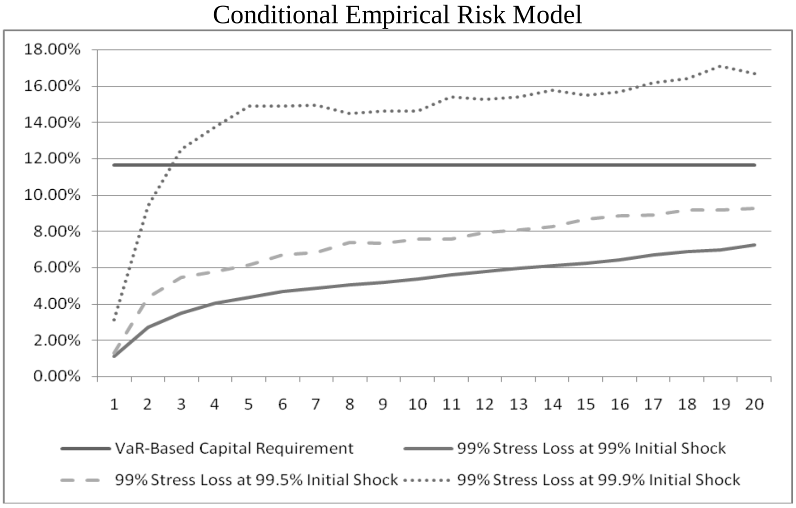
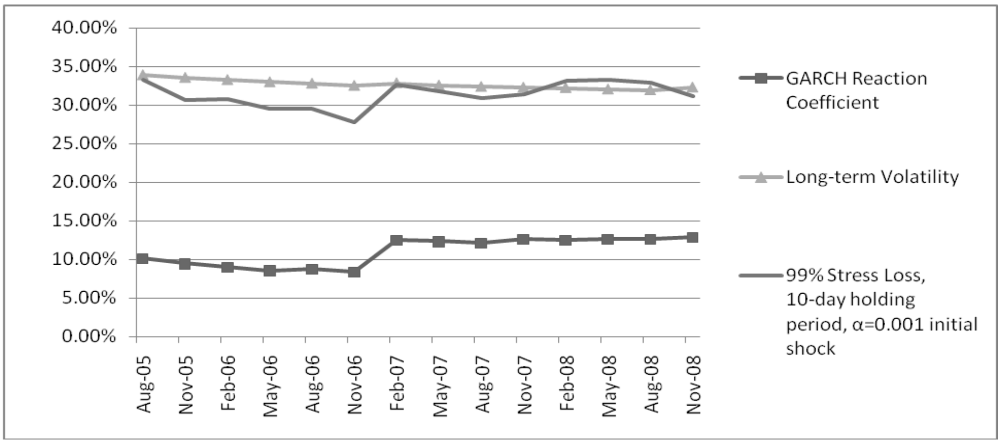


Figure 5

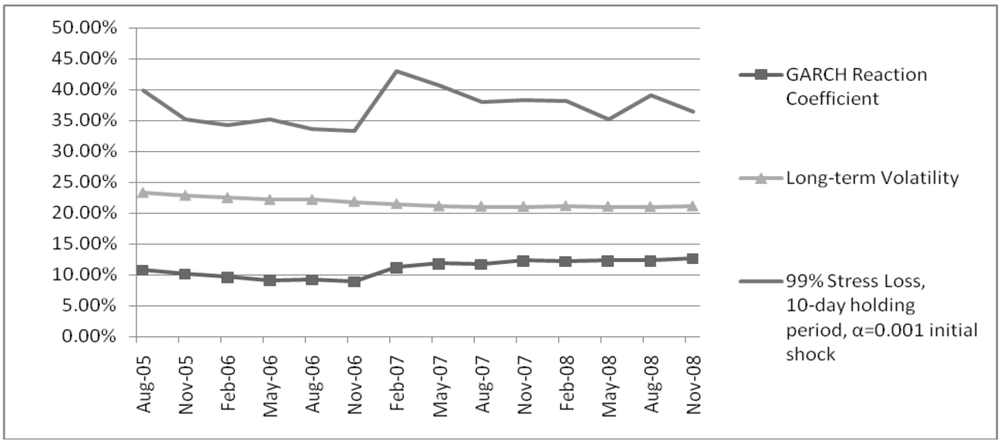
SET50 index Stress Test Analysis over Time for Initial Shock α=0.001

We use 10 years of data, i.e., August 1995 to August 2005 to estimate long term volatility, the reaction term of the GARCH equation (γ_2), and other necessary parameters of each model. The stress loss is estimated quarterly using all available data since the first data to the estimation point. The horizontal axis represents quarter of estimation, and the vertical axis represents percentage of portfolio value.

Conditional Normal Risk Model



Conditional Student's *t* Risk Model



Conditional Empirical Risk Model

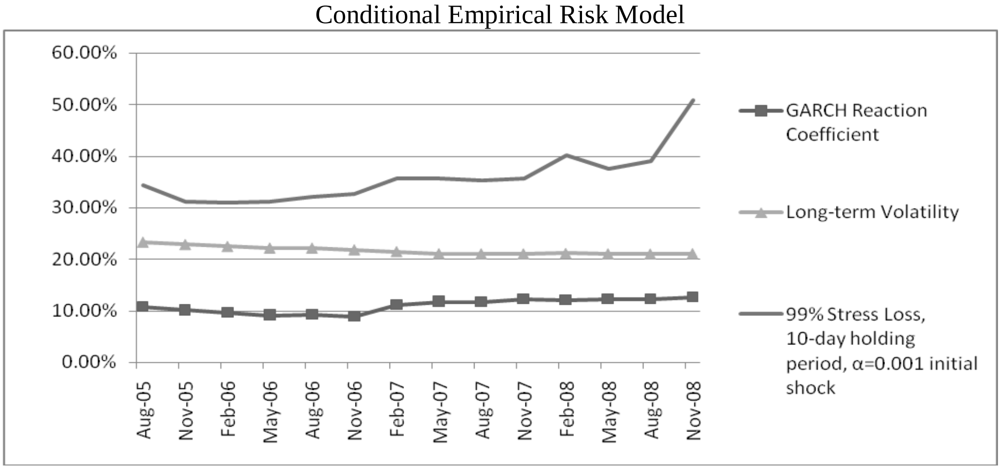
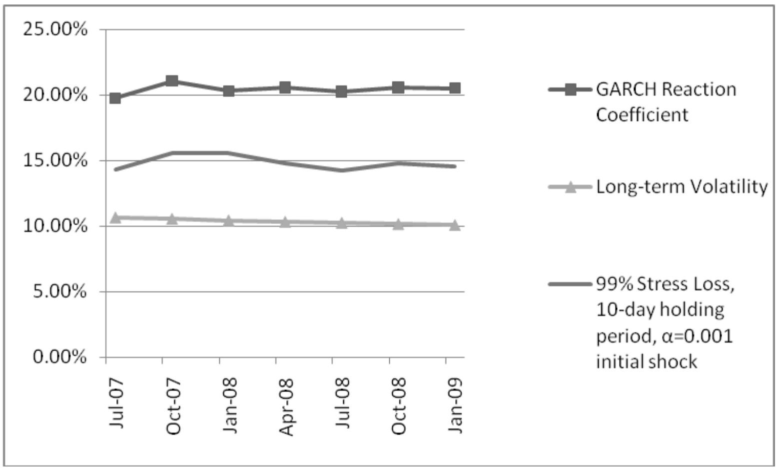


Figure 6

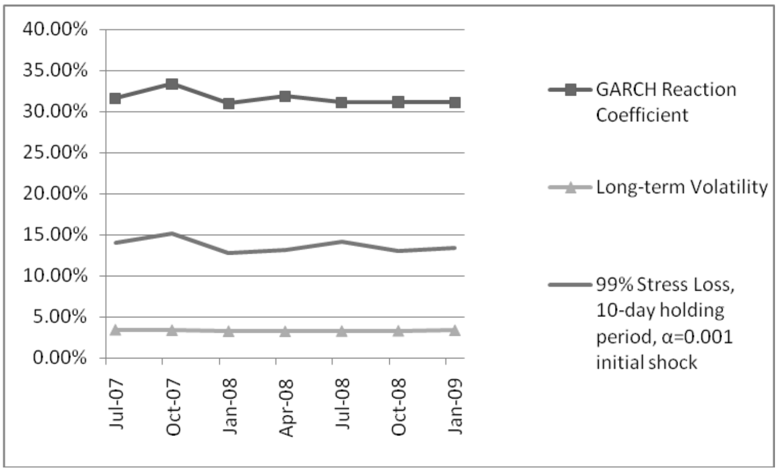
Long USD/ Short THB Stress Test Analysis over Time for Initial Shock α=0.001

We use 10 years of data, i.e., July 1997 to July 2007 to estimate long term volatility, the reaction term of the GARCH equation (γ_2), and other necessary parameters of each model. The stress loss is estimated quarterly using all available data since the first data to the estimation point. The horizontal axis represents quarter of estimation, and the vertical axis represents percentage of portfolio value.

Conditional Normal Risk Model



Conditional Student's *t* Risk Model



Conditional Empirical Risk Model

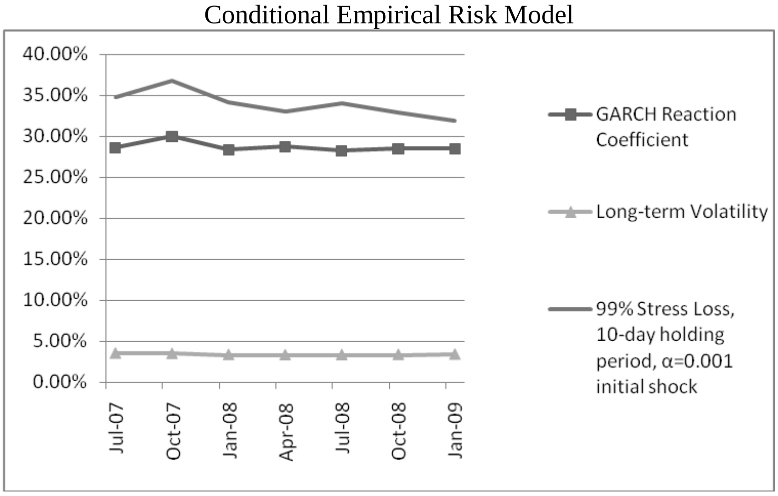
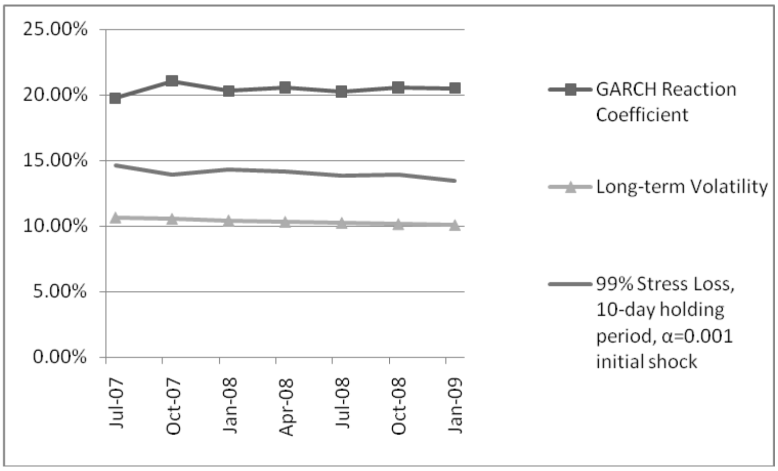


Figure 7

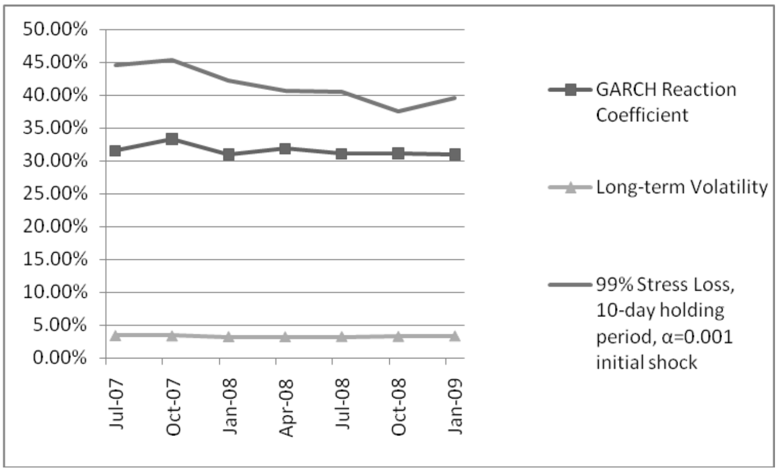
Short USD/Long THB Stress Test Analysis over Time for Initial Shock α=0.001

We use 10 years of data, i.e., July 1997 to July 2007 to estimate long term volatility, the reaction term of the GARCH equation (γ_2), and other necessary parameters of each model. The stress loss is estimated quarterly using all available data since the first data to the estimation point. The horizontal axis represents quarter of estimation, and the vertical axis represents percentage of portfolio value.

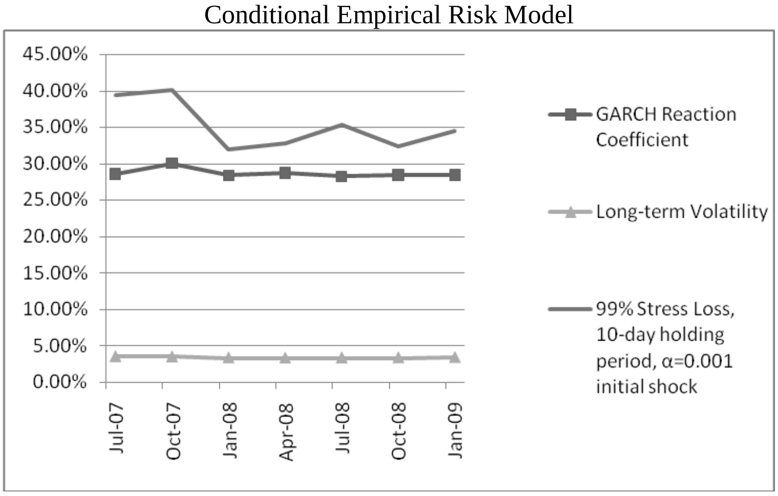
Conditional Normal Risk Model



Conditional Student's *t* Risk Model



Conditional Empirical Risk Model



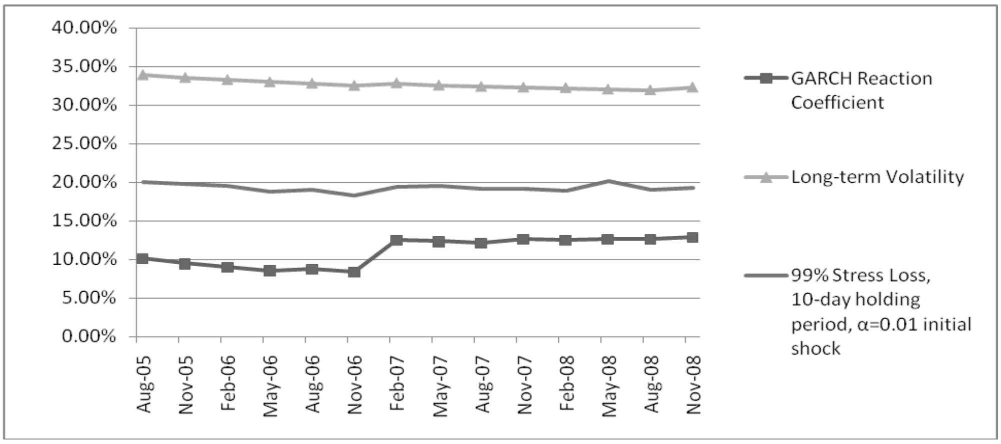
Appendix

Figure A-1

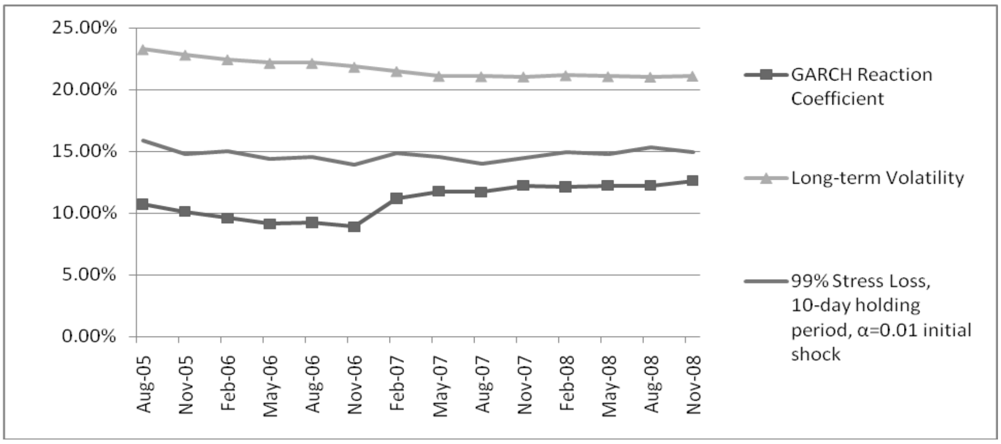
SET50 index Stress Test Analysis over Time for an Initial Shock α =0.01

We use 10 years of data, i.e., August 1995 to August 2005 to estimate long term volatility, the reaction term of the GARCH equation (γ_2), and other necessary parameters of each model. The stress loss is estimated quarterly using all available data since the first data to the estimation point. The horizontal axis represents quarter of estimation, and the vertical axis represents percentage of portfolio value.

Conditional Normal Risk Model



Conditional Student's *t* Risk Model



Conditional Empirical Risk Model

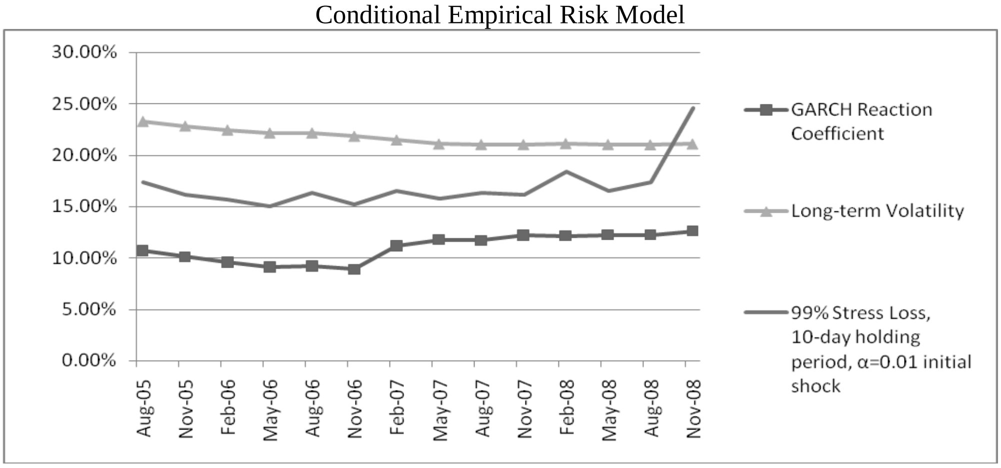
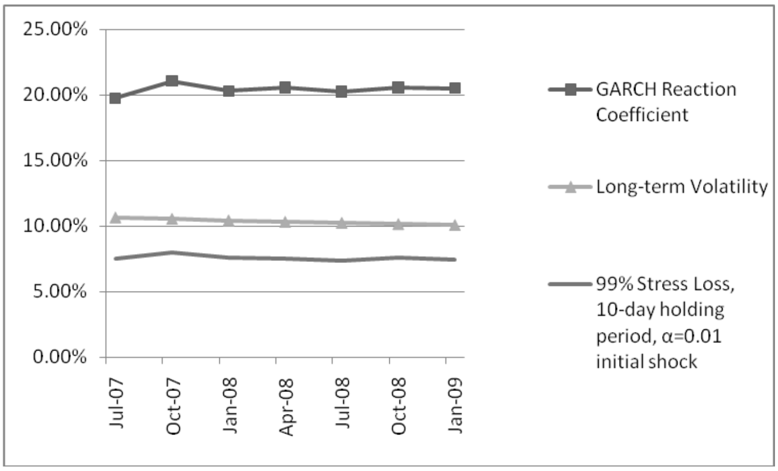


Figure A-2

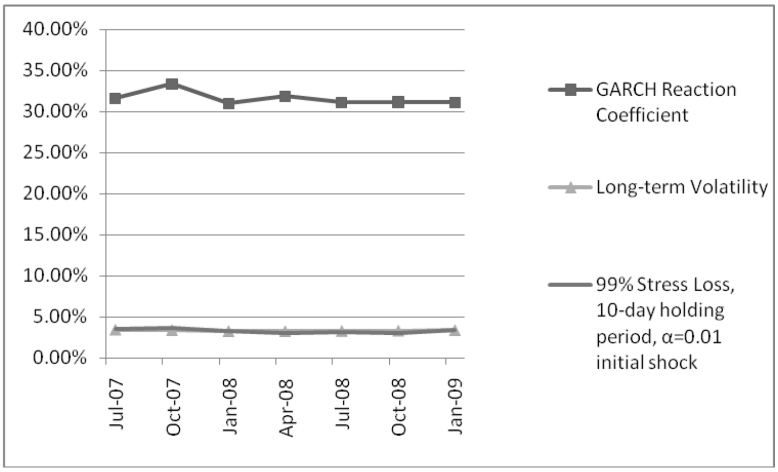
Long USD/ Short THB Stress Test Analysis over Time for an Initial Shock α =0.01

We use 10 years of data, i.e., July 1997 to July 2007 to estimate long term volatility, the reaction term of the GARCH equation (γ_2), and other necessary parameters of each model. The stress loss is estimated quarterly using all available data since the first data to the estimation point. The horizontal axis represents quarter of estimation, and the vertical axis represents percentage of portfolio value.

Conditional Normal Risk Model



Conditional Student's *t* Risk Model



Conditional Empirical Risk Model

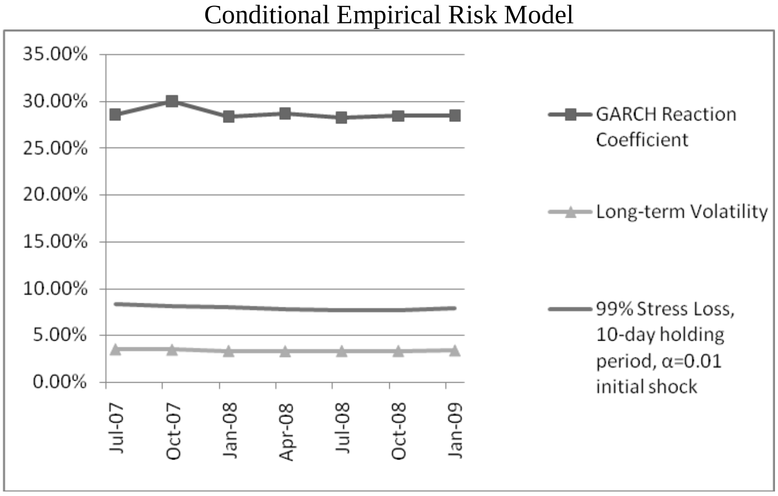
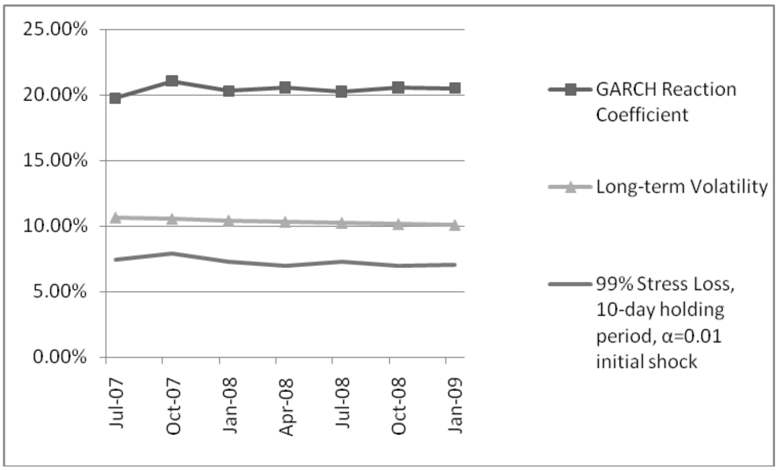


Figure A-3

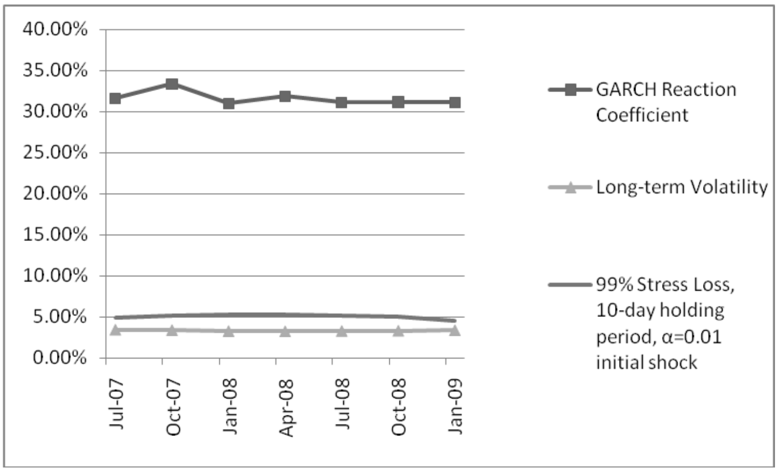
Short USD/Long THB Stress Test Analysis over Time for an Initial Shock α =0.01

We use 10 years of data, i.e., July 1997 to July 2007 to estimate long term volatility, the reaction term of the GARCH equation (γ_2), and other necessary parameters of each model. The stress loss is estimated quarterly using all available data since the first data to the estimation point. The horizontal axis represents quarter of estimation, and the vertical axis represents percentage of portfolio value.

Conditional Normal Risk Model



Conditional Student's *t* Risk Model



Conditional Empirical Risk Model